### Practice Lab: CNN for CIFAR10

Training cifar 10 Dataset with a CNN model (using tensorflow)

## **Outline**

- Packages
- Loading Data
  - Dataset overview
- Modeling
  - MLP
  - CNN
- Evaluating

### 1 - Packages

```
In [53]:
          import numpy as np
          import pandas as pd
          import tensorflow as tf
          import matplotlib.pyplot as plt
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense, Conv2D, MaxPool2D, Flatten,BatchNormalizatio
          from tensorflow.keras.callbacks import EarlyStopping
          from tensorflow.keras import layers, models
          from sklearn.metrics import confusion matrix , classification report
          from keras.layers import AveragePooling2D
          from keras.layers import GlobalMaxPooling2D
          from keras.layers import GlobalAveragePooling2D
          from tensorflow.keras.utils import to categorical
          import seaborn as sns
          from keras.utils import plot model
```

### 2 - Loading Data

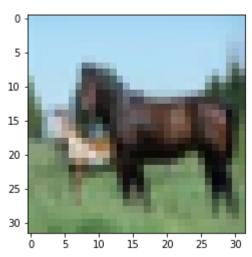
```
In [3]: (x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
```

#### **Dataset overview**

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

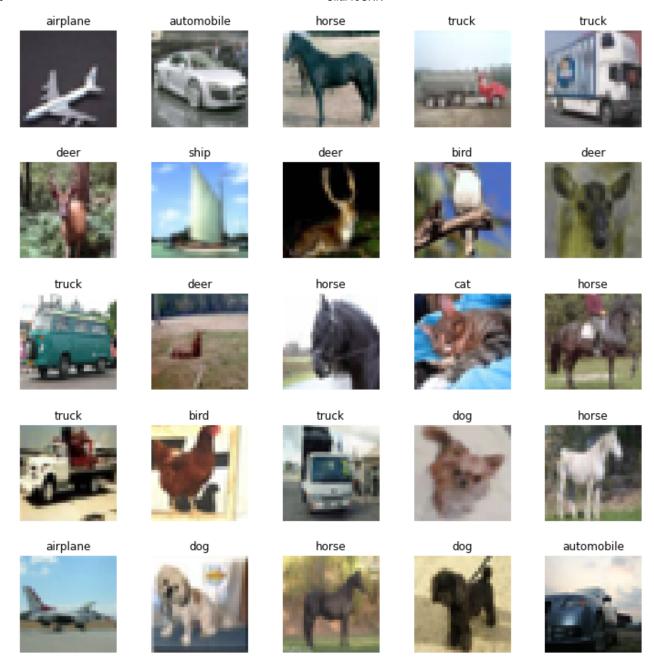
The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

```
In [3]:
           x_train[0].shape
          (32, 32, 3)
 Out[3]:
 In [4]:
           y_train.size
          50000
 Out[4]:
 In [5]:
           x_train.size
          153600000
 Out[5]:
 In [6]:
           np.unique(y_train)
          array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
 Out[6]:
In [37]:
           labels = ["airplane"
           ,"automobile"
             "bird"
             "cat"
            "deer"
            "dog"
            "frog"
           ,"horse"
            "ship"
           ,"truck"]
         Plotting
 In [8]:
           plt.imshow(x train[12])
           print(labels[int(y_train[12])])
          horse
```



```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
X = x_train
fig, axes = plt.subplots(5,5, figsize=(10,10))
fig.tight_layout(pad=0.1)

for i,ax in enumerate(axes.flat):
    random_index = np.random.randint(50000)
    ax.imshow(X[random_index], cmap='gray')
    ax.set_title(labels[int(y_train[random_index])])
    ax.set_axis_off()
```



## 3 - Modeling

First we should Normalize our date

```
In [4]: x_train = x_train / 255.0 x_test = x_test / 255.0
```

In [2]: #Classification report

Define classificationReport method :

#### Precision

Is the ability of a classifier not to label an instance positive that is actually negative. For each class it is defined as the ratio of true positives to the sum of true and false positives.

### Recall

The ability of a classifier to correctly find all positive instances. For each class, it is defined as the ratio of true positives to the sum of true positives and false negatives.

### F1-score

The F1 score is a weighted harmonic mean of precision and recall such that the best score is 1.0 and the worst is 0.0.

```
def ClassificationReport(model):
    y_pred = model.predict(x_test)
    y_pred_classes = [np.argmax(element) for element in y_pred]
    print("Classification Report: \n", classification_report(y_test, y_pred_classes))
```

# 3.1 - simple MLP model:

```
In [15]:
       mlp = models.Sequential([
             layers.Flatten(input_shape=(32,32,3)),
             layers.Dense(2048, activation='relu'),
             layers.Dense(1024, activation='relu'),
             layers.Dense(10, activation='softmax')
          1)
       mlp.compile(optimizer='SGD',
                 loss='sparse categorical crossentropy',
                 metrics=['accuracy'])
       mlp.fit(x_train, y_train, epochs=5)
       Epoch 1/5
       3528
       Epoch 2/5
       4241
       Epoch 3/5
       4541
       Epoch 4/5
       1563/1563 [================ ] - 47s 30ms/step - loss: 1.4916 - accuracy: 0.
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
```

```
Out[15]: <keras.callbacks.History at 0x210f022a9d0>
```

| 313/313 [] - 23 OIIIS/SCEP |           |        |          |         |  |
|----------------------------|-----------|--------|----------|---------|--|
| Classification             | Report:   |        |          |         |  |
|                            | precision | recall | f1-score | support |  |
|                            |           |        |          |         |  |
| 0                          | 0.58      | 0.53   | 0.55     | 1000    |  |
| 1                          | 0.41      | 0.82   | 0.54     | 1000    |  |
| 2                          | 0.29      | 0.50   | 0.37     | 1000    |  |
| 3                          | 0.44      | 0.23   | 0.30     | 1000    |  |
| 4                          | 0.43      | 0.31   | 0.36     | 1000    |  |
| 5                          | 0.44      | 0.35   | 0.39     | 1000    |  |
| 6                          | 0.51      | 0.55   | 0.53     | 1000    |  |
| 7                          | 0.62      | 0.45   | 0.52     | 1000    |  |
| 8                          | 0.58      | 0.65   | 0.61     | 1000    |  |
| 9                          | 0.66      | 0.26   | 0.37     | 1000    |  |
|                            |           |        |          |         |  |
| accuracy                   |           |        | 0.46     | 10000   |  |
| macro avg                  | 0.49      | 0.46   | 0.45     | 10000   |  |

0.46

0.45

10000

0.49

Now we use CNN model

weighted avg

### 3.2 - **CNN**

```
metrics=['accuracy'])
     cnn.fit(x train, y train, epochs=5)
     Epoch 1/5
     4982
     Epoch 2/5
     6318
     Epoch 3/5
     6818
     Epoch 4/5
     7183
     Epoch 5/5
     <keras.callbacks.History at 0x2110a34dfd0>
Out[27]:
In [28]:
      cnn.evaluate(x_test,y_test)
     [0.9776250123977661, 0.6693000197410583]
Out[28]:
In [39]:
      cnn.summary()
     Model: "sequential 3"
      Layer (type)
                     Output Shape
                                    Param #
     _____
      conv2d (Conv2D)
                      (None, 30, 30, 32)
                                    896
      max pooling2d (MaxPooling2D (None, 15, 15, 32)
      )
      conv2d_1 (Conv2D)
                      (None, 13, 13, 64)
                                    18496
      max pooling2d 1 (MaxPooling (None, 6, 6, 64)
      2D)
      flatten_3 (Flatten)
                     (None, 2304)
      dense 9 (Dense)
                      (None, 128)
                                    295040
      dense 10 (Dense)
                      (None, 10)
                                    1290
     Total params: 315,722
     Trainable params: 315,722
     Non-trainable params: 0
```

```
In [30]:
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js_size=(3, 3), activation='relu', input_shape=(32, 3)
```

```
layers.MaxPooling2D((2, 2)),
          layers.Conv2D(filters=64, kernel size=(3, 3), activation='relu'),
          layers.MaxPooling2D((2, 2)),
          layers.Flatten(),
          layers.Dense(128, activation='relu'),
          layers.Dense(10, activation='softmax')
       ])
In [38]:
       cnn64.compile(optimizer='adam',
                 loss='sparse categorical_crossentropy',
                 metrics=['accuracy'])
       cnn.fit(x_train, y_train, epochs=5)
       Epoch 1/5
       4808
       Epoch 2/5
       6230
       Epoch 3/5
       6707
       Epoch 4/5
       6999
       Epoch 5/5
       7256
       <keras.callbacks.History at 0x2110cffc6d0>
Out[38]:
In [40]:
       cnn64.evaluate(x_test,y_test)
       [0.9196601510047913, 0.684499979019165]
Out[40]:
In [41]:
       ClassificationReport(cnn64)
       313/313 [========= ] - 3s 9ms/step
       Classification Report:
                 precision
                         recall f1-score
                                      support
              0
                    0.73
                          0.71
                                 0.72
                                        1000
              1
                    0.82
                          0.80
                                 0.81
                                        1000
              2
                    0.64
                          0.50
                                 0.56
                                        1000
              3
                    0.55
                          0.47
                                 0.51
                                        1000
              4
                    0.65
                          0.56
                                 0.60
                                        1000
              5
                          0.59
                                 0.58
                   0.58
                                        1000
              6
                   0.69
                          0.81
                                 0.74
                                        1000
              7
                   0.71
                          0.73
                                 0.72
                                        1000
              8
                    0.79
                          0.82
                                 0.80
                                        1000
              9
                    0.66
                          0.85
                                 0.74
                                        1000
                                 0.68
                                       10000
         accuracy
         macro ave
                    0.68
                                 0.68
                                       10000
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
```

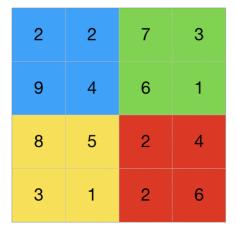
weighted avg 0.68 0.68 0.68 10000

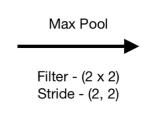
```
In [48]:
      cnn32 = Sequential([
        layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(32, 3)
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dense(10, activation='softmax')
      ])
In [49]:
      cnn32.compile(optimizer='adam',
               loss='sparse categorical crossentropy',
               metrics=['accuracy'])
      cnn32.fit(x_train, y_train, epochs=5)
      Epoch 1/5
      4231
      Epoch 2/5
     5671
      Epoch 3/5
      Epoch 4/5
      6534
     Epoch 5/5
      <keras.callbacks.History at 0x21108487190>
Out[49]:
```

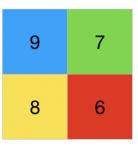
# Types of Pooling Layers

```
In [75]: #Max pooling (32)
```

Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter. Thus, the output after max-pooling layer would be a feature map containing the most prominent features of the previous feature map.







```
In [76]:
       cnn_MaxPooling32 = Sequential([
          layers.Conv2D(filters=32, kernel size=(3, 3), activation='relu', input shape=(32, 3)
          layers.MaxPooling2D((2, 2)),
          layers.Flatten(),
          layers.Dense(128, activation='relu'),
          layers.Dense(10, activation='softmax')
       1)
In [77]:
       cnn MaxPooling32.compile(optimizer='adam',
                 loss='sparse categorical crossentropy',
                 metrics=['accuracy'])
       cnn_MaxPooling32.fit(x_train, y_train, epochs=5)
       Epoch 1/5
       4859
       Epoch 2/5
       5963
       Epoch 3/5
       Epoch 4/5
       6765
       Epoch 5/5
       <keras.callbacks.History at 0x211371d2df0>
Out[77]:
      accuracy: 0.7027
In [78]:
       #Max pooling (64)
In [79]:
       cnn MaxPooling64 = Sequential([
          layers.Conv2D(filters=64, kernel size=(3, 3), activation='relu', input shape=(32, 3)
          layers.MaxPooling2D((2, 2)),
          layers.Flatten(),
          lavone Danco (128 activation - 'ralu'),
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
```

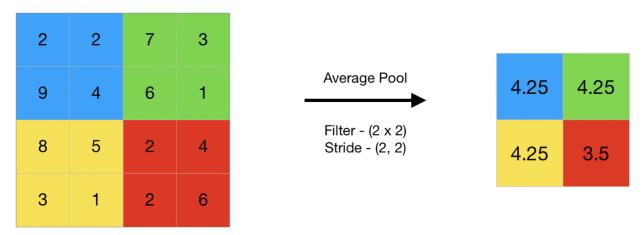
```
layers.Dense(10, activation='softmax')
])
```

I use a bigger epoch number for this model because it was too close to average pooling

```
In [100...
  cnn_MaxPooling64.compile(optimizer='adam',
      loss='sparse categorical crossentropy',
      metrics=['accuracy'])
  cnn_MaxPooling64.fit(x_train, y_train, epochs=20)
  Epoch 1/20
  9780
  Epoch 2/20
  9801
  Epoch 3/20
  9817
  Epoch 4/20
  Epoch 5/20
  9812
  Epoch 6/20
  9817
  Epoch 7/20
  1563/1563 [================ ] - 37s 23ms/step - loss: 0.0614 - accuracy: 0.
  9810
  Epoch 8/20
  9824
  Epoch 9/20
  9842
  Epoch 10/20
  9849
  Epoch 11/20
  9823
  Epoch 12/20
  9836
  Epoch 13/20
  9872
  Epoch 14/20
  9834
  Epoch 15/20
  9867
  Epoch 16/20
```

In [72]: #Average pooling

Average pooling computes the average of the elements present in the region of feature map covered by the filter. Thus, while max pooling gives the most prominent feature in a particular patch of the feature map, average pooling gives the average of features present in a patch.



```
In [81]:
          cnn AveragePooling = Sequential([
             layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu', input_shape=(32, 3)
             AveragePooling2D(pool_size = 2, strides = 2),
             layers.Flatten(),
             layers.Dense(128, activation='relu'),
             layers.Dense(10, activation='softmax')
          ])
In [101...
          cnn_AveragePooling.compile(optimizer='adam',
                       loss='sparse categorical crossentropy',
                       metrics=['accuracy'])
          cnn_AveragePooling.fit(x_train, y_train, epochs=20)
         Epoch 1/20
         9804
         Epoch 2/20
                                           ====] - 34s 22ms/step - loss: 0.0597 - accuracy: 0.
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```

```
Epoch 3/20
9825
Epoch 4/20
Epoch 5/20
9838
Epoch 6/20
9827
Epoch 7/20
9848
Epoch 8/20
9856
Epoch 9/20
9866
Epoch 10/20
9841
Epoch 11/20
9865
Epoch 12/20
9849
Epoch 13/20
9873
Epoch 14/20
9853
Epoch 15/20
9877
Epoch 16/20
9855
Epoch 17/20
9875
Epoch 18/20
9876
Epoch 19/20
9881
Epoch 20/20
9903
<keras.callbacks.History at 0x21136e45460>
```

loss: 0.0327 - accuracy: 0.9903

Out[101...

```
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js #GLobal pooling
```

Global pooling reduces each channel in the feature map to a single value. Thus, an nh x nw x nc feature map is reduced to 1 x 1 x nc feature map. This is equivalent to using a filter of dimensions nh x nw i.e. the dimensions of the feature map.

```
In [178...
       cnn_GlobalPooling = Sequential([
          layers.Conv2D(filters=64, kernel size=(3, 3), activation='relu', input shape=(32, 3)
          layers.GlobalAveragePooling2D(),
          layers.Flatten(),
          layers.Dense(128, activation='relu'),
          layers.Dense(10, activation='softmax')
       1)
In [179...
       cnn GlobalPooling.compile(optimizer='adam',
                loss='sparse_categorical_crossentropy',
                metrics=['accuracy'])
       cnn_GlobalPooling.fit(x_train, y_train, epochs=5)
       2330
       Epoch 2/5
       1563/1563 [================ ] - 17s 11ms/step - loss: 1.7967 - accuracy: 0.
       3192
       Epoch 3/5
       3510
       Epoch 4/5
       3646
      Epoch 5/5
       <keras.callbacks.History at 0x2112101b0a0>
Out[179...
      accuracy: 0.3740
In [102...
       cnn_AveragePooling.evaluate(x_test,y_test)
       [4.334970951080322, 0.6108999848365784]
Out[102...
In [103...
       cnn_MaxPooling64.evaluate(x_test,y_test)
       [4.2817840576171875, 0.6205999851226807]
Out[103...
In [114...
       #Let's combine these for the best result
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
```

```
layers.Conv2D(filters=64, kernel size=(3, 3), activation='relu', input shape=(32, 3)
       BatchNormalization(),
       AveragePooling2D(pool size = 2, strides = 2),
       layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu', input_shape=(32, 3)
       layers.MaxPooling2D((2, 2)),
       layers.Flatten(),
       layers.Dense(512,activation='relu'),
       layers.Dense(10, activation='softmax')
     ])
 In [7]:
     cnn Final.compile(optimizer='adam',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])
     cnn_Final.fit(x_train, y_train, epochs=15)
     Epoch 1/15
     5557
     Epoch 2/15
     1563/1563 [================ ] - 59s 38ms/step - loss: 0.8956 - accuracy: 0.
     6872
     Epoch 3/15
     7587
     Epoch 4/15
     8137
     Epoch 5/15
     8719
     Epoch 6/15
     9128
     Epoch 7/15
     9323
     Epoch 8/15
     1563/1563 [================ ] - 67s 43ms/step - loss: 0.1448 - accuracy: 0.
     9492
     Epoch 9/15
     9571
     Epoch 10/15
     9610
     Epoch 11/15
     Epoch 12/15
     9704
     Epoch 13/15
     9708
     Epoch 14/15
     Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
```

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Cifar10CNN 9724 <keras.callbacks.History at 0x1a418071e20> Out[7]: In [115... #First try In [111... cnn Final.summary() Model: "sequential 29" Layer (type) Output Shape Param # conv2d\_47 (Conv2D) (None, 30, 30, 64) 1792 average pooling2d 8 (Averag (None, 15, 15, 64) ePooling2D) conv2d\_48 (Conv2D) (None, 13, 13, 64) 36928 max pooling2d 32 (MaxPoolin (None, 6, 6, 64) g2D) flatten 27 (Flatten) (None, 2304) dense 66 (Dense) (None, 128) 295040 batch normalization (BatchN (None, 128) 512 ormalization) dense 67 (Dense) (None, 10) 1290 Total params: 335,562 Trainable params: 335,306 Non-trainable params: 256 loss: 0.4474 - accuracy: 0.8409 In [116... #Second try In [117... cnn Final.summary() Model: "sequential 30" Output Shape Layer (type) Param # \_\_\_\_\_\_ conv2d 49 (Conv2D) (None, 30, 30, 64) 1792 average\_pooling2d\_9 (Averag (None, 15, 15, 64) ePooling2D) conv2d 50 (Conv2D) (None, 13, 13, 64) 36928

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```
Cifar10CNN
         g2D)
         flatten_28 (Flatten)
                                 (None, 2304)
         dense 68 (Dense)
                                 (None, 256)
                                                       590080
         dense 69 (Dense)
                                 (None, 10)
                                                       2570
        ______
        Total params: 631,370
        Trainable params: 631,370
        Non-trainable params: 0
       loss: 0.1076 - accuracy: 0.9618
In [127...
        #Third Try
In [126...
         cnn Final.summary()
        Model: "sequential 32"
         Layer (type)
                                 Output Shape
                                                       Param #
        ______
         conv2d 57 (Conv2D)
                                 (None, 30, 30, 64)
                                                       1792
         average_pooling2d_13 (Avera (None, 15, 15, 64)
         gePooling2D)
         conv2d 58 (Conv2D)
                                 (None, 13, 13, 64)
                                                       36928
         max_pooling2d_37 (MaxPoolin (None, 6, 6, 64)
         g2D)
         flatten_32 (Flatten)
                                 (None, 2304)
         dense_75 (Dense)
                                 (None, 256)
                                                       590080
         dense 76 (Dense)
                                 (None, 128)
                                                       32896
         dense_77 (Dense)
                                 (None, 10)
                                                       1290
        _____
        Total params: 662,986
        Trainable params: 662,986
        Non-trainable params: 0
       loss: 0.1673 - accuracy: 0.9415
In [128...
        # 4th try
In [131...
```

localhost:8888/nbconvert/html/Desktop/tree/SBU/t5/شبكه عصبي/assignments/2/Cifar10CNN.ipynb?download=false

cnn Final.summary()

dal. "cacuantial 22" Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

| Layer (type)  | Output Shape       | Param # |
|---|--------------------|---------|
| conv2d_59 (Conv2D)                                      | (None, 30, 30, 64) | 1792    |
| <pre>average_pooling2d_14 (Avera<br/>gePooling2D)</pre> | (None, 15, 15, 64) | 0       |
| conv2d_60 (Conv2D)                                      | (None, 13, 13, 64) | 36928   |
| <pre>max_pooling2d_38 (MaxPoolin g2D)</pre>             | (None, 6, 6, 64)   | 0       |
| flatten_33 (Flatten)                                    | (None, 2304)       | 0       |
| dense_78 (Dense)  | (None, 512)        | 1180160 |
| dense_79 (Dense)  | (None, 10)         | 5130    |
|   |                    | ======= |

Total params: 1,224,010 Trainable params: 1,224,010 Non-trainable params: 0

loss: 0.0787 - accuracy: 0.9730

In [136...

# 5th try

In [137... cnn\_Final.summary()

Model: "sequential\_35"

| Layer (type)  | Output Shape       | Param # |
|---|--------------------|---------|
| conv2d_63 (Conv2D)                                      |                    | 1792    |
| <pre>average_pooling2d_16 (Avera<br/>gePooling2D)</pre> | (None, 15, 15, 64) | 0       |
| conv2d_64 (Conv2D)                                      | (None, 13, 13, 64) | 36928   |
| <pre>max_pooling2d_40 (MaxPoolin g2D)</pre>             | (None, 6, 6, 64)   | 0       |
| flatten_35 (Flatten)                                    | (None, 2304)       | 0       |
| dense_83 (Dense)  | (None, 1024)       | 2360320 |
| <pre>batch_normalization_1 (Batch_Normalization)</pre>  | (None, 1024)       | 4096    |
| dense_84 (Dense)  | (None, 512)        | 524800  |
| dense_85 (Dense)  | (None, 10)         | 5130    |

Non-trainable params: 2,048

loss: 0.2206 - accuracy: 0.9224

In [14]:

#Final try

In [15]:

cnn\_Final.summary()

Model: "sequential 1"

| Layer (type)   | Output Shape                            | Param #  |
|--|---|----------|
| conv2d_2 (Conv2D)                                      | (None, 30, 30, 64)                      | 1792     |
| <pre>batch_normalization_1 (Batc hNormalization)</pre> | (None, 30, 30, 64)                      | 256      |
| <pre>average_pooling2d_1 (Averag ePooling2D)</pre>     | (None, 15, 15, 64)                      | 0        |
| conv2d_3 (Conv2D)                                      | (None, 13, 13, 64)                      | 36928    |
| <pre>max_pooling2d_1 (MaxPooling 2D)</pre>             | (None, 6, 6, 64)                        | 0        |
| flatten_1 (Flatten)                                    | (None, 2304)                            | 0        |
| dense_2 (Dense)  | (None, 512)                             | 1180160  |
| dropout (Dropout)                                      | (None, 512)                             | 0        |
| dense_3 (Dense)  | (None, 10)                              | 5130     |
| =======================================                | ======================================= | ======== |

------

Total params: 1,224,266 Trainable params: 1,224,138 Non-trainable params: 128

# 4 - Let's evaluate our model

```
313/313 [========== ] - 6s 18ms/step
Classification Report:
               precision
                            recall f1-score
                                               support
           0
                             0.73
                                       0.74
                   0.74
                                                 1000
           1
                   0.84
                             0.80
                                       0.82
                                                 1000
           2
                   0.57
                             0.57
                                       0.57
                                                 1000
           3
                   0.46
                             0.52
                                       0.48
                                                 1000
           4
                   0.69
                             0.57
                                       0.62
                                                 1000
           5
                             0.56
                   0.57
                                       0.57
                                                 1000
           6
                   0.70
                             0.81
                                       0.75
                                                 1000
           7
                   0.76
                             0.70
                                       0.73
                                                 1000
           8
                   0.77
                             0.83
                                       0.80
                                                 1000
           9
                   0.78
                             0.75
                                       0.77
                                                 1000
                                       0.68
    accuracy
                                                10000
                                       0.68
                                                10000
   macro avg
                   0.69
                             0.68
weighted avg
                   0.69
                                       0.68
                                                10000
                             0.68
```

As you can see we got a big loss number for testing data

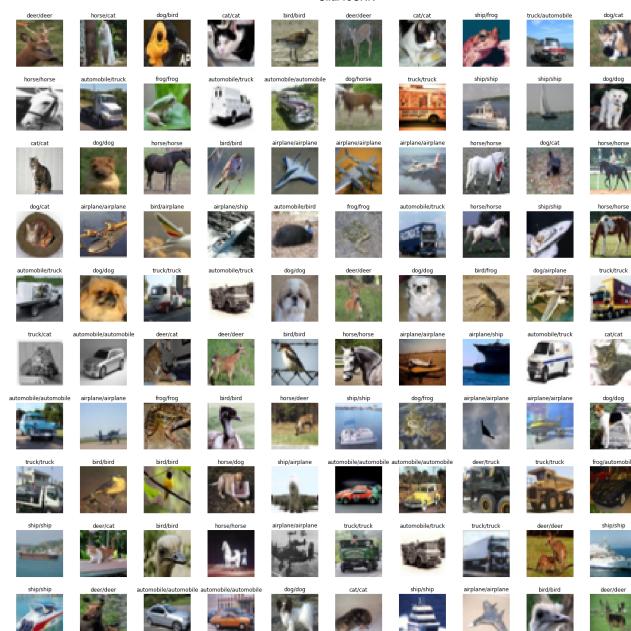
Now we prevent overfitting for our model

```
In [23]:
        cnn Final = Sequential([
           layers.Conv2D(filters=64, kernel size=(3, 3), activation='relu', input shape=(32, 3)
           BatchNormalization(),
           AveragePooling2D(pool size = 2, strides = 2),
           layers.Conv2D(filters=64, kernel size=(3, 3), activation='relu', input shape=(32, 3)
           layers.MaxPooling2D((2, 2)),
           layers.Flatten(),
           layers.Dense(512,activation='relu'),
           Dropout(0.5),
           layers.Dense(10, activation='softmax')
        ])
In [24]:
        cnn Final.compile(optimizer='adam',
                   loss='sparse categorical crossentropy',
                   metrics=['accuracy'])
In [25]:
        history = cnn_Final.fit(x_train, y_train, validation_data=(x_test, y_test), epochs=7, b
        Epoch 1/7
        260 - val loss: 2.2226 - val accuracy: 0.3002
        Epoch 2/7
        703 - val_loss: 2.1073 - val_accuracy: 0.4955
        Epoch 3/7
        322 - val loss: 1.3993 - val accuracy: 0.6226
        712 - val loss: 0.9649 - val accuracy: 0.6710
       Epoch 5/7
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js == ] - 49s 290ms/step - loss: 0.8643 - accuracy: 0.6
        9/9 - val_loss: 0.9692 - val_accuracy: 0.6629
```

```
Epoch 6/7
                228 - val_loss: 0.8960 - val_accuracy: 0.6911
                Epoch 7/7
                420 - val loss: 0.9560 - val accuracy: 0.6789
               Try with binary cross entropy
 In [19]:
                  y_categorical_train = to_categorical(y_train, 10)
                  y_categorical_test = to_categorical(y_test, 10)
 In [26]:
                  cnn_Final.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy
 In [28]:
                  history = cnn_Final.fit(x_train, y_categorical_train, validation_data=(x_test, y_categorical_train, y_categorical_train_train_train_train_train_train_train_train_train_trai
                Epoch 1/7
                561 - val_loss: 0.8966 - val_accuracy: 0.6960
                Epoch 2/7
                788 - val loss: 0.8495 - val accuracy: 0.7120
                Epoch 3/7
                995 - val loss: 0.8333 - val accuracy: 0.7230
                Epoch 4/7
                132 - val loss: 0.8315 - val accuracy: 0.7213
                282 - val_loss: 0.8431 - val_accuracy: 0.7282
                Epoch 6/7
                435 - val loss: 0.8508 - val accuracy: 0.7348
                Epoch 7/7
                548 - val loss: 0.9347 - val accuracy: 0.7089
 In [29]:
                  Y prediction = cnn Final.predict(x test)
                313/313 [============ ] - 4s 11ms/step
 In [30]:
                  Y prediction.shape
                 (10000, 10)
 Out[30]:
 In [31]:
                  Y prediction
                array([[2.23211202e-04, 5.51889316e-05, 1.63338453e-04, ...,
 Out[31]:
                             8.09079211e-05, 7.35946838e-03, 4.46087643e-06],
                            [7.68834725e-03, 3.08940606e-03, 9.68137073e-08, ...,
                             2.80909296e-10, 9.89222050e-01, 6.19801526e-08],
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js 2, 8.07335135e-03, ...,
                              <del>7.33093423e-03, 0.00331280e-0</del>1, 1.98803213e-03],
```

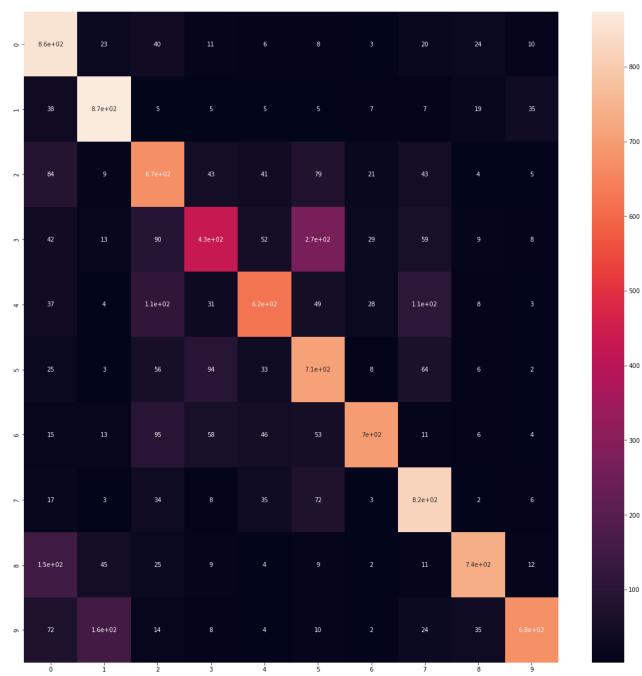
```
[8.19458066e-08, 2.57242959e-07, 2.24625575e-04, ...,
                  6.04846049e-03, 1.22072993e-06, 1.16995146e-07],
                 [3.10936980e-02, 5.96647933e-02, 4.47810907e-03, ...,
                  5.71781397e-03, 2.54460581e-04, 6.01701288e-07],
                 [7.11552605e-12, 5.51200578e-13, 9.32100264e-08, ...,
                  9.99882936e-01, 1.24371059e-14, 6.78344672e-11]], dtype=float32)
In [32]:
          classes x = np.argmax(Y prediction, axis=1)
In [34]:
          classes x.shape
          (10000,)
Out[34]:
In [65]:
          warnings.simplefilter(action='ignore', category=FutureWarning)
          X = x \text{ test}
          fig, axes = plt.subplots(10,10, figsize=(20,20))
          fig.tight layout(pad=0.1)
          print("Model Predict/Reality")
          for i,ax in enumerate(axes.flat):
              random_index = np.random.randint(10000)
              ax.imshow(X[random_index], cmap='gray')
              ax.set title(labels[int(classes x[random index])]+"/" +labels[int(y test[random ind
              ax.set_axis_off()
```

Model Predict/Reality



In [52]:

plt.figure(figsize=(20, 20))
sns.heatmap(confusion\_matrix(y\_test, classes\_x), annot=True)
plt.show()



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